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Multi-retailer Sales Model under Uncertain Demand in a Pharmaceutical Two-Echelon Supply Chain with Vendor Managed Inventory System

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Abstract. The Vendor Managed Inventory (VMI) system enables vendors to manage their own and their retailers' inventories to improve the performance of two-echelon supply chains. However, most VMI systems consider the demand patterns of the retailers as deterministic, which is uncommon in practice where variability is significant. This can lead to inefficient results, particularly within the pharmaceutical industry where an efficient supply chain through VMI is vital. The present work proposes a multi-retailer VMI model to maximize the profits of a two-echelon supply chain in the presence of non-deterministic or uncertain demand. Due to the complexity of the model, a micro-genetic algorithm was developed to determine the lot size strategy considering the variability of the non-deterministic demand within the profit function and reduce the stockout risk. Through computer simulation, the proposed VMI model was tested, showing that it is more efficient to reduce stockout events than those using deterministic demand patterns.

Keywords: Vendor Managed Inventory, continuous review, genetic algorithms

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1 Introduction

Vendor Managed Inventory (VMI) is an inventory management strategy developed to improve supply chain (SC) performance [1], [2]. With VMI, the vendor or manufacturer directly manages the inventories at its retailers' and/or buyers' warehouses [3]. This enables continuous tracking of inventories to determine the most appropriate time to produce them, distribute them and supply them as their levels decrease by the clients' purchase behavior [4].

For an efficient implementation of VMI, collaboration and policies are established through contracts to ensure that information flow and flexible production and distribution planning throughout the SC are performed accordingly to the retailers' requirements and vendors' capabilities. This leads to reduce the operational costs of the SC and distribute the benefits fairly among all its members [1], [5], [6]. This represents an advantage when compared to the traditional SC, where most of the agreements between SC members (first/second level suppliers/vendors, wholesalers or retailers, etc.) are non-cooperative with no mutual benefit, favoring only the interests of one member (vendor or retailer) [6].

Although the vendors' market competitiveness and cooperation between retailers and vendors are positively associated with the use of VMI systems, such benefits could vary depending on the implementation strategy [7], [8]. Thus, for specific industries, the operational models and technologies considered to support the VMI system must be carefully selected, designed and adapted to ensure a successful implementation.
Within the pharmaceutical industry, vendors and retailers require high stock availability and service level as medicines are vital for human health and survival [9]. Traditionally, high inventory levels are maintained to guarantee the availability of these

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products. However, this practice can increase inventory management costs and obsolescence risks when medicines have short expiry dates [10]. Also, stockout risk is significant as shortage is common [9].

Even though these problems and risks are widely known, there is limited data regarding the application of VMI systems within the pharmaceutical industry. In this regard, a VMI system can improve collaboration, information exchange and cost reduction between hospitals, drug/medicine distributors and laboratories [11], [12].

Hence, the present work contributes with the development of a VMI system for two-echelon pharmaceutical SCs. The proposed VMI model considers a key aspect which has not been addressed by previous works (i.e., [13], [14]) and is associated with stockout and obsolescence risks in practice: demand variability (i.e., non-deterministic or uncertain demand). This aspect is integrated within the profit function of the two-echelon SC to determine the economic lot size required to reduce the inventory management costs and stockout risks. Due to the complexity of the profit function, a micro-genetic algorithm (μGA) was developed to solve it to near optimality and determine the lot size that maximizes profits and minimizes stockout risks. Finally, through computer simulation, the VMI model was tested, showing that it is more efficient to reduce stockout events than those using constant (i.e., deterministic) demand patterns. This testing is frequently absent from other works in the field.

The structure of the present work is as follows: in Section 2 the base or reference VMI model is reviewed and described. This is the model of Diabat (2014) [13]. Then, in Section 3, our proposed or extended VMI model is described. The details of the μGA developed to solve the profit functions of the VMI models are presented in Section 4. The results of the μGA and the proposed VMI model are analyzed in Section 5. Finally, our conclusions and future work are discussed in Section 6.

2 Reference Model Review

Diabat (2014) [13] developed a profit (P) mathematical model that integrated the price-demand and inventory control costs for a two-echelon SC with a VMI system. This model considers the variables and mathematical formulations described in Table 1.

This model was based on the works reported in [15] and [16], and it has been extended by Seifbarghy et al. (2016) [17] and Salehi-Amiri et al. (2020) [14]. Thus, it is an established model within the VMI literature.

3. Proposed Extended Model

The model described in Table 1 considers deterministic demand patterns within the inventory costs for the mathematical formulation [14], [17]. This may compromise the estimation of the economic lot size, defined by the decision variable y_j, in the presence of variable (non-deterministic) demand patterns.

To overcome this aspect, the integration of an inventory control model with non-deterministic demand is considered. Because the reduction of stockout risks is imperative within the pharmaceutical industry, frequent tracking of the inventory levels is required. For this case, the Continuous Review or (Q, R) inventory control model for non-deterministic demand was considered [18], [19]. In general terms, this model considers the variables and mathematical formulations described in Table 2.

To integrate the extended model, a standardization of terms is performed between the mathematical formulations of inventory management costs and decision variables. First, the economic lot size under the (Q, R) model is standardized as follows (at this point, S_{bj} and H_{bj} are generalized as S_b and H_b respectively):

$$Q = \sqrt{\frac{2D(C_o+pn)}{C_h}} = \sqrt{\frac{2y(S_s+S_b+pn)}{H_s+H_b}} . \quad \textbf{(1)}$$

Table 1. Notation and mathematical formulation of the reference VMI two-echelon profit model [13]

Variable	Description
a_j	intercept value of the cost-demand curve of the *j*-th retailer
b_j	negative slope of the cost-demand curve of the *j*-th retailer
y_j	decision variable = annual sales quantity of the *j*-th retailer
δ	production cost per unit
θ_j	flow cost per unit from vendor to the *j*-th retailer
H_s	annual unit holding cost of the vendor in independent mode
H_{bj}	annual unit holding cost of the *j*-th retailer in independent mode
S_s	setup cost of the vendor per order in independent mode
S_{bj}	setup cost of the *j*-th retailer per order in independent mode
y_{jmin}	minimum expected sales quantity of the *j*-th retailer
y_{jmax}	maximum expected sales quantity of the *j*-th retailer
C	capacity of the vendor
H	total inventory management costs = $H = \sqrt{2y_j(H_s + H_{bj})(S_s + S_{bj})}$

Profit Mathematical Formulation

$$Maximize\ P = \sum_{j=1}^{N}\{a_j y_j - b_j y_j^2 - \delta y_j - 0.5\theta_j y_j^2 - H\}$$

Subject to:

$$y_{jmin} < y_j < y_{jmax},$$
$$\sum_{j=1}^{N} y_j \leq C$$
$$y_j \geq 0$$

Second, the mathematical formulation of *H* (total inventory management costs, see Table 1) is extended by the model described in (1). As reported in [13], [15], [16], *H* represents the total costs associated to inventory management, which under the (Q, R) model are defined by *TC* (see Table 2). As consequence, the equivalent mathematical expression for *H* is obtained by replacing the updated expressions of *Q* and *R* into *TC* as follows:

$$H = \left(\frac{y}{\sqrt{\frac{2y(S_S+S_b+p\sigma_{LT}L(z))}{H_S+H_b}}}\right)(S_s + S_b) + \left(\frac{H_s+H_b}{2}\right)\sqrt{\frac{2y(S_S+S_b+p\sigma_{LT}L(z))}{H_S+H_b}} + (H_s + H_b)[z\sigma_{LT} + \sigma_{LT}L(z)] + p\sigma_{LT}L(z)\left(\frac{y}{\sqrt{\frac{2y(S_S+S_b+p\sigma_{LT}L(z))}{H_S+H_b}}}\right). \quad \textbf{(2)}$$

$$H = \left(\frac{y}{\sqrt{\frac{2y(S_s+S_b+p\sigma_{LT}L(z))}{H_s+H_b}}}\right)(S_s + S_b + p\sigma_{LT}L(z)) + \left(\frac{H_s+H_b}{2}\right)\sqrt{\frac{2y(S_s+S_b+p\sigma_{LT}L(z))}{H_s+H_b}} + (H_s + H_b)[z\sigma_{LT} + \sigma_{LT}L(z)] \,. \quad \textbf{(3)}$$

Table 2. Notation and mathematical formulation of the (Q, R) inventory control model with non-deterministic demand [18], [19]

Variable	Description
D	cumulative demand through a planning horizon
p	cost of a unit of product not delivered to a customer or retailer (unit stockout cost)
n	expected number of units not delivered to a customer or retailer (number of stockout units) and it is estimated by as $n = \sigma_{LT}L(z)$,
μ_{LT}	average demand throughout the lead time ($\mu_{LT} = d \times LT$)
σ_{LT}	standard deviation of the demand throughout the lead time (σ_{LT}=$\sigma\sqrt{LT}$)
L(z)	probability given by the loss function associated to stockout units
d	average daily demand
σ	standard deviation of the daily demand
Q	decision variable = optimal lot size (economic lot quantity) to deliver to retailer
R	reorder point = inventory level which triggers the ordering process of a lot of size Q ($R = \mu_{LT} + z\sigma_{LT}$)
C_o	ordering cost associated to a lot of size Q (note that C_o is equivalent to $S_S + S_{bj}$ from the reference VMI model)
C_h	holding cost associated to a stored unit of product within the inventory (note that C_h is equivalent to $H_S + H_{bj}$ from the reference VMI model)
LT	lead time (delivery time to supplier)
Lot Size Mathematical Formulation	$Q = \sqrt{\frac{2D(C_o + pn)}{C_h}}$
Total Inventory Management Cost Mathematical Formulation	$TC = \left(\frac{D}{Q}\right)C_o + \left(\frac{Q}{2}\right)C_h + C_h[R - \mu_{LT} + \sigma_{LT}L(z)] + pn\left(\frac{D}{Q}\right)$

$$H = \left(\frac{y\sqrt{H_s+H_b}}{\sqrt{2y(S_s+S_b+p\sigma_{LT}L(z))}}\right)(S_s + S_b + p\sigma_{LT}L(z)) + \frac{\sqrt{y(H_s+H_b)(S_s+S_b+p\sigma_{LT}L(z))}}{\sqrt{2}} + (H_s + H_b)[z\sigma_{LT} + \sigma_{LT}L(z)] \,. \quad \textbf{(4)}$$

$$H = \left(\frac{\sqrt{y(H_s+H_b)(S_s+S_b+p\sigma_{LT}L(z))}}{\sqrt{2}}\right) + \frac{\sqrt{y(H_s+H_b)(S_s+S_b+p\sigma_{LT}L(z))}}{\sqrt{2}} + (H_s + H_b)[z\sigma_{LT} + \sigma_{LT}L(z)] \,. \quad \textbf{(5)}$$

$$H = \sqrt{2y(H_s + H_b)(S_s + S_b + p\sigma_{LT}L(z))} + (H_s + H_b)(z\sigma_{LT} + \sigma_{LT}L(z)) \,. \quad \textbf{(6)}$$

In contrast to the reference model (see Table 1), the updated mathematical expression for H (6) includes σ_{LT} which provides information regarding demand variability. For non-deterministic demand, the variability is considered larger (as measured by the daily standard deviation σ) than a fraction h of the average daily demand (d). This is measured by the Coefficient of Variability (CV) which is defined as:

$$CV = \frac{\sigma}{d} \geq h \ . \tag{7}$$

In terms of demand variability:

$$\sigma_{LT} = \sigma\sqrt{LT} = hd\sqrt{LT} \ . \tag{8}$$

Finally, to reduce the stockout risk, y must include the additional items associated with demand variability. This is equivalent to $y \rightarrow x+z\sigma_{LT}$ where x is a supporting variable which leads to the following updated profit mathematical formulation for j=1, …, N retailers (P from Table 1):

$$Maximize\ P = \sum_{j=1}^{N}\left\{a_j\left(x_j + z_j hd_j\sqrt{LT_j}\right) - b_j\left(x_j + z_j hd_j\sqrt{LT_j}\right)^2 - \delta\left(x_j + z_j hd_j\sqrt{LT_j}\right) - 0.5\theta_j\left(x_j + z_j hd_j\sqrt{LT_j}\right)^2 - \left[\sqrt{2\left(x_j + z_j hd_j\sqrt{LT_j}\right)\left(H_s + H_{bj}\right)\left(S_s + S_{bj} + p_j hd_j\sqrt{LT_j}L(z_j)\right)} + \left(H_s + H_{bj}\right)\left(z_j hd_j\sqrt{LT_j} + hd_j\sqrt{LT_j}L(z_j)\right)\right]\right\}. \tag{9}$$

Subject to:

$$y_{jmin} < x_j + z_j hd_j\sqrt{LT_j} < y_{jmax} \quad \forall j \tag{10}$$

$$\sum_{j=1}^{N}\left(x_j + z_j hd_j\sqrt{LT_j}\right) \leq C \tag{11}$$

$$x_j + z_j hd_j\sqrt{LT_j} \geq 0 \quad \forall j \tag{12}$$

$$x_j \geq 0 \tag{13}$$

4. Solving Method: Micro-Genetic Algorithm

Determining the values of x_j or y_j which maximize the profit function P is a complex task. Because of this, the works reviewed on VMI systems for two-echelon SC have developed metaheuristics to determine these values and solve the P function to near optimality and within reasonable computational time. Among these metaheuristics the following can be mentioned: Genetic-Algorithm / Simulated Annealing [13], Particle Swarm Optimization [14], Genetic Algorithm [15], Particle Swarm Optimization / hybrid Genetic Algorithm + Artificial Immune System [16], discrete Particle Swarm Optimization / Genetic Algorithm / Simulated Annealing [17].

The present work considers the development of a metaheuristic based on Genetic Algorithms to solve the P function. In contrast to the reviewed works which considered Genetic Algorithms, our proposal is focused on a lean and faster version of this metaheuristic.

Figure 1 presents the general structure of the micro-Genetic Algorithm (μGA) developed to solve the P function. While the μGA has the same structure than a standard GA, the difference is established within the selection of three main features: chromosome coding of solutions, population size of solutions, and reproduction operators for solution. These features can lead the μGA to achieve faster convergence to near optimal solutions by considering smaller populations and thus, less storing memory [20], [21]. Figure 2 presents the details of the chromosome coding for the population and Figure 3 prsents the details of the reproduction operators used for the μGA.

As presented in Figure 2, a solution consists of the set of y_j values for the N retailers of the two-schelon SC. The assessment of these values is performed through their substitution within the profit function P. Within the μGA, the value of P is used to measure the fitness of the solution for selection and reproduction of new solutions. Initially, a population with M solutions (or individuals) is randomly generated considering the limits defined by y_{jmin} and y_{jmax} for each y_j value.

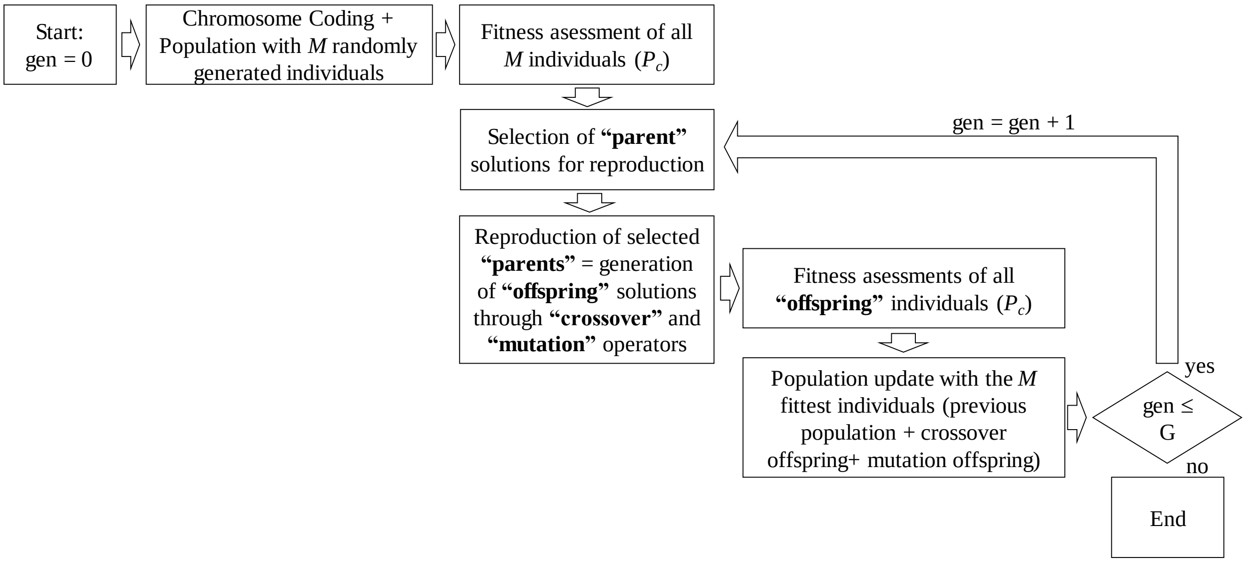


Fig. 1. Structure of the μGA developed to solve the profit model for the two-echelon VMI SC

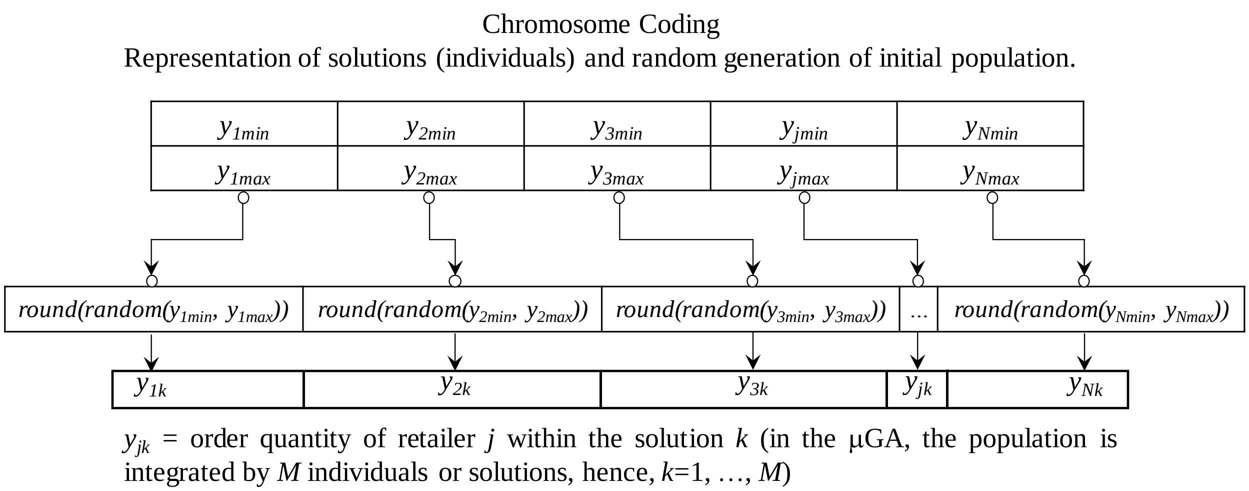


Fig. 2. Chromosome coding considered to generate initial solutions and populations for the proposed μGA

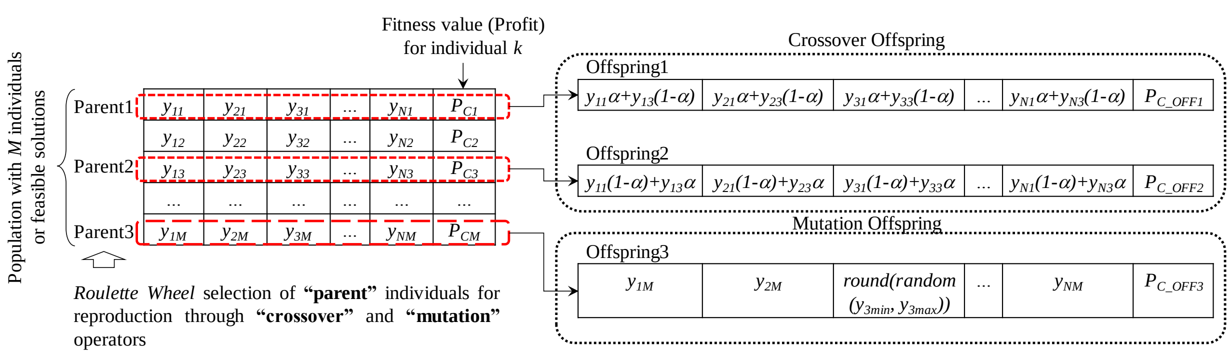


Fig. 3. Selection and reproduction operators considered to generate new solutions and populations for the proposed μGA

Then, as presented in Figure 2, P is computed for each solution and selection of "parents" is performed to create new "offspring" solutions. Selection is performed by the *Roulette Wheel* operator, and reproduction is performed by linear crossover and mutation operators. Once that the "offspring" solutions are created, their respective P values are computed.

Finally, the population is updated with the best M solutions (those with the highest P values) from the current population and the crossover and mutation offspring solutions. If a stop condition is met, the process is finished, otherwise, the selection and reproduction processes continue with the updated population. The proposed μGA considers a stop condition given by a fixed number of iterations or generations ($gen \leq G$).

The μGA was coded in MATLAB 2018a and executed in a HP Workstation with Intel Xeon CPU E3-1240 at 3.40 GHz and 8GB RAM. The parameters of the μGA were the following: crossover probability (α) = 0.3, total number of generations (G) = 100, population size (M) = 20 individuals, number of crossover and mutation offspring = $2M/3$ individuals.

5. Results

5.1 Assessment of the Micro-Genetic Algorithm

Assessment of the μGA was performed with the data presented in Table 3. This data was considered by (Diabat, 2014) [13] to evaluate the reference model for P (see Table 1) and compared with three solving methods: LINGO (exact method), standard GA and hybrid algorithm (metaheuristics).

Table 3. Test data of the reference VMI two-echelon profit model [13]

Retailer Related Data			
j	1	2	3
H_{bj}	7	8	9
S_{bj}	10	20	30
a_j	20	19	18
b_j	0.003	0.005	0.008
y_{jmin}	2000	500	500
y_{jmax}	4000	3000	1500
θ_j	0.004	0.006	0.008
Vendor Related Data			
H_s		9	
S_s		15	
C		5750	
δ		7	

Table 4 presents the results of the solving methods reported by [13]. The results of the proposed μGA are included for comparison purposes. As presented, the μGA outperformed the standard GA and the hybrid algorithm reported by [13], achieving near optimal results (close to LINGO). Thus, the μGA can provide near-optimal solutions for the extended model described by the mathematical formulation (9)-(13) for P.

Table 4. Results with the test data of the reference VMI two-echelon profit model [13]

Solving Method	y_1	y_2	y_3	P
LINGO	2000	710	500	9903.10
GA	2002	673	500	9878.09
Hybrid	2001	675	500	9886.52
μGA	2001	710	501	9893.87

5.2 Solving the Extended Two-Echelon VMI Model

For the assessment of the proposed model for P, Table 5 presents the set of parameters for the demand patterns of the retailers. Note that high demand variability ($CV = h = 0.5$) is considered. Table 6 presents the results of the reference model and the proposed model with non-deterministic demand data.

Table 5. Test data for the extended VMI two-echelon profit model (own data)

j	1	2	3
d_j	20	25	30
h	0.5	0.5	0.5
LT_j	5	10	15
p_j	8	10	15
z_j	2.17	1.65	2.32
$L(z_j)$	0.005	0.021	0.003

Table 6. Results of test data for the reference and extended VMI two-echelon profit model

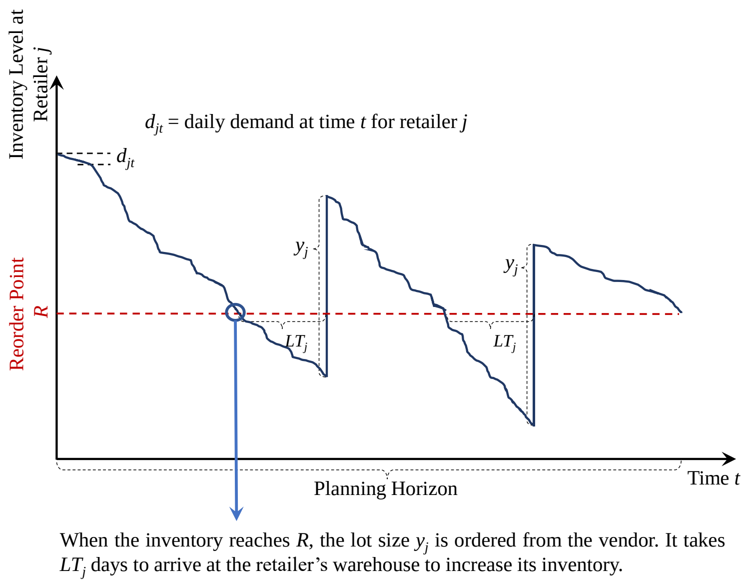
VMI Models	y_1	y_2	y_3	R_1	R_2	R_3	P
Reference	2001	675	501	149	316	585	9886.52
Extended VMI	2021	710	555	149	316	585	7817.82

As presented, P in the extended VMI model is smaller than P in the reference model. This is expected on account of the additional costs included in the extended VMI model which is focused on reducing the stockout risk in the presence of non-deterministic demand (risk not considered by the reference model). The reorder points R_j, which depend on the average demands and demand variabilities (independent of costs), are the same for both models.

5.3 Validating the Extended Two-Echelon VMI Model through Simulation

It is expected that the quantities y_j determined by the μGA under the extended VMI model can reduce the stockout risks in comparison to the reference model. However, this cannot be assessed by only considering the mathematical formulation and the profit results. This is because the proposed model assumes variable demand, and this can only be assessed through a time-dependent system.

In this context, discrete-event simulation provides the tool to represent processes as a (discrete) sequence of events in time. In the two-echelon VMI system, the process consists of the inventory consumption – supply cycle at the *j*-th retailer, where inventory is consumed at a variable daily demand rate. This process can be described by the pseudo-code presented in Figure 4.




```
Input data from retailer j: d_j, σ_j, z_j, LT_j, R_j, y_j
Planning Horizon: T days
Inventory = y_j + R_j
count_LT = 0
for t=0 until t=T do
    d_jt = |d_j + random(-z_j, z_j)×σ_j|
    if Inventory – d_jt > R do
        Inventory = Inventory – d_jt
    else do
        Inventory = Inventory – d_jt
        count_LT = count_LT+1
    end
    if count_LT = LT_j+1 do
        Inventory = Inventory + y_j
        count_LT = 0
    end
end
```

Fig. 4. Description and pseudocode of the inventory consumption – supply cycle at the *j*-th retailer

The simulation pseudocode was implemented with the MATLAB/Octave programming platform based on the code described in [19]. Figure 5 presents an overview of the computational code. As presented, the input data consists of d_j, σ_j (=hd_j), R_j, y_j and LT_j. Then, the code randomly generates daily normally-distributed demand to simulate the replenishment and consumption patterns of the inventory at any time t through a planning horizon (in this case, $k = 270$ working days). At the end, the code plots these patterns and determines the number of days with stockout events (where inventory < daily demand).

It should be noted that simulation involves a random element to provide variable demand values. Hence, a different demand pattern is obtained with each execution of the simulation code.

Therefore, the validation of solutions of the reference and extended VMI two-echelon profit models was performed with 10 runs of the simulation code. Table 7 and Table 8 presents the number of days with stockout considering the parameters of the reference and extended VMI two-echelon profit models respectively.

As presented, stockout events can occur in the scenarios modelled by the reference and the extended VMI models. However, it is important to highlight that the number of events is significantly smaller with the parameters of the extended VMI model. In the presence of variable demand rate, the parameters of the reference model led to 2+4+2 = 8 stockout events for retailer 2, and 1+4+20+4+2+4 = 35 stockout events for retailer 3 through all 10 simulation runs. In contrast, the parameters of the extended model led to 1+1+1 = 3 and 2+3 = 5 stockout events for retailer 2 and 3 respectively.

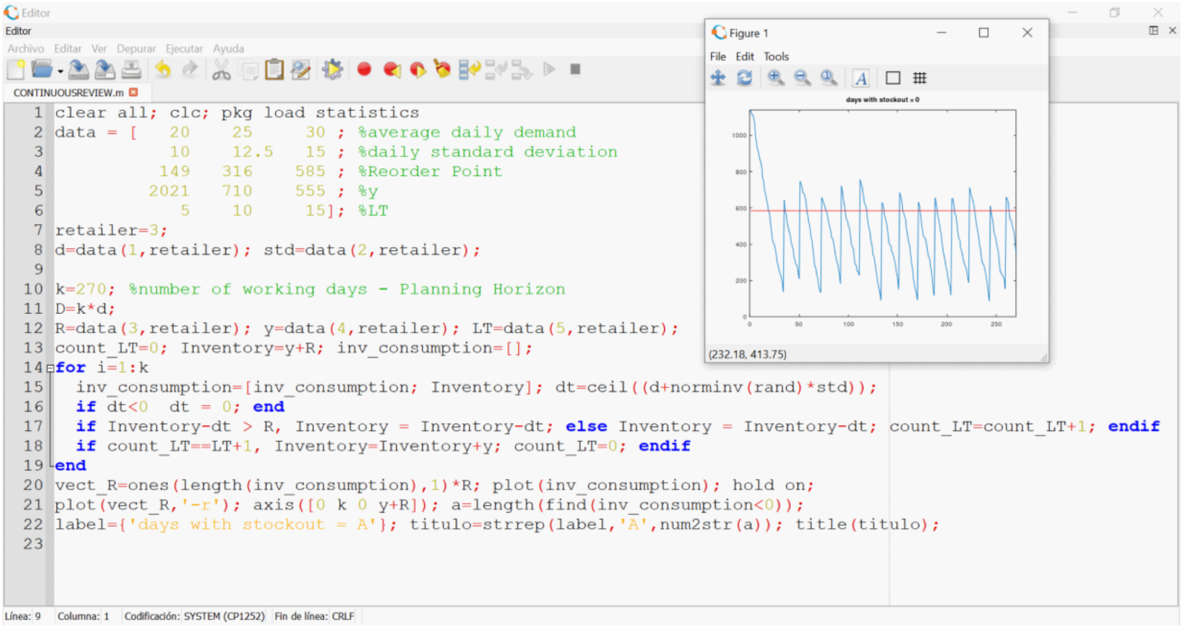


Fig. 5. Implementation of the simulation pseudocode code for the assessment of the reference and extended VMI two-echelon profit models

Table 7. Number of days with stockout considering the parameters y_j for the reference VMI two-echelon profit model: y_1 = 2001, y_2 = 675, y_3 = 501 (see Table 6)

Retailer *J*	Simulation Runs									
	1	2	3	4	5	6	7	8	9	10
1	0	0	0	0	0	0	0	0	0	0
2	2	0	0	4	0	0	0	0	2	0
3	1	4	0	20	0	0	4	0	2	4

Table 8. Number of days with stockout considering the parameters y_j for the extended VMI two-echelon profit model: y_1 = 2021, y_2 = 710, y_3 = 555 (see Table 6)

Retailer *j*	Simulation Runs									
	1	2	3	4	5	6	7	8	9	10
1	0	0	0	0	0	0	0	0	0	0
2	0	0	0	1	0	0	1	0	0	1
3	0	0	0	0	2	0	3	0	0	0

6. Conclusions and Future Work

Traditionally, maintaining high inventory levels has been the only way to guarantee the availability of vital products in the pharmaceutical industry. However, this may increase inventory management costs, obsolescence and stockout risks when medicine has short expiry date or a highly variable demand.

The present research proposed a multi-retailer VMI sales model with the premise of non-deterministic demand as shortage risks are correlated with demand variability. The solutions and parameters (inventory lot sizes and reorder points) obtained with this model were dynamically evaluated through computer simulation. By integrating data regarding demand variability within the profit function of the VMI system, the estimated inventory lots and reorder points can reduce the periods with stockout in the two-echelon SC.

While these results are encouraging to reduce stockout risks in SC, it is important to provide short- and medium-term follow-up to the application of these models on the aimed industries. Also, to increase the complexity of the model to include variables such as the products' shelf life for perishable products in the agro-food industry.

Data Availability Statement

The authors confirm that the data supporting the findings of this study are available within the article. If specific data or supplementary materials are required, these can be provided by the corresponding author SOCM upon reasonable request.

Competing Interest Statement

In accordance with Taylor & Francis policy and our ethical obligation as researchers, we confirm that there are no relevant financial or non-financial competing interests to report.

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